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EDGE-BASED TEXTURE MEASURES.(U)

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EDGE-BASED TEXTURE MEASURES

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ABSTRACT

A class of texture measures is introduced based on first-order statistics derived from edges in the image. These measures are related to the generalized cooccurrence features of Davis et al. They yield good discriminations among textures on perceptually plausible grounds.

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1. Introduction

A wide variety of measures for discriminating visual textures have been studied; see [1] for a review. Traditional approaches involve measures based on the autocorrelation, or equivalently, on the Fourier power spectrum; measures derived from second-order gray level probability densities (gray level cooccurrence matrices); and measures derived from first-order probability densities of local feature values (e.g., gray level difference histograms). These measures are computed on a pixel by pixel basis; they do not take into account the fact that perceptually, textures often appear to be composed of "primitives" (i.e., uniform microregions).

Maleson et al. [2] proposed an approach to texture analysis based on extracting primitives and computing their properties (e.g., average gray level, area, eccentricity, etc.). He considered texture measures derived from first- or second-order probability densities of such properties, where the second-order densities are defined in terms of neighboring pairs of primitives. Wang et al. [3] investigated a similar approach in which simple methods of extracting the primitives were used (e.g., thresholding at a percentile, or adaptive quantization), and Hong et al. [4] studied an edge-based method of primitive extraction.

In previous primitive-based approaches, it is assumed that the primitives are small connected regions, and properties of these regions are used as a basis for defining texture measures. In many situations, this assumption is not entirely realistic.

We can perceive primitives in a texture if the texture contains edges that link into local "clusters," even though these clusters of edges do not surround connected regions. Thus, it would be better not to use properties of primitives (area, average gray level, etc.) that depend on the primitives being extracted as connected regions.

This paper proposes a class of texture measures derived from properties of edges and pairs of edges detected in the given texture. The properties include the curvature of an edge, as well as the average gray level, distance, contrast difference and slope difference between a pair of facing edges. Texture measures are derived from the first-order probability densities of these properties. These measures yield good discrimination among textures based on perceptually plausible differences among them.

There is a close relationship between our edge-based texture measures and the measures based on generalized cooccurrence matrices (GCMs) introduced by Davis et al. [5-6; see also 7]. The GCM approach is based on cooccurrences of local properties satisfying given spatial constraint predicates. In particular, GCMs have usually been defined in terms of pairs of edges having given orientations and occurring in given relative positions, e.g., extending or facing each other. Our measures too are defined in terms of edges, and make use of their orientation and relative position; but they also use other properties of the edges, and involve first-order rather than second-order probability densities.

Section 2 of this paper defines a set of edge-based texture measures, and Section 3 illustrates their ability to discriminate among various types of textures.

2. Measures

Two types of measures were used in our experiments; one type was derived from pairs of "facing" edges, and the other from edge curvature. The computation of these measures is described in the following paragraphs.

2.1. Edge pairs

To reduce the number of edges from which the edge pair measures are derived, the image is first smoothed using two iterations of median filtering over a 3-by-3 neighborhood of each pixel, and the gray levels are linearly rescaled (if necessary) to the range 0-31. Edges are then detected by applying the eight 3-by-3 masks

$$\begin{matrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{matrix}\ , \quad \begin{matrix} 1 & 1 & 0 \\ 1 & 0 & -1 \\ 0 & -1 & -1 \end{matrix}\ , \ \ldots$$

at every pixel, picking the mask yielding the highest output value, and thresholding the result at 11 (i.e., discarding values ≤ 10). The same masks (with various thresholds) were used in the edge-based texture primitive extraction experiments of [4]. The slope of a detected edge is defined by the mask that gives the highest output. In addition to the thresholding, nonmaxima are suppressed in the gradient direction - i.e., an edge response is discarded if there is a higher response at a neighboring pixel in the direction perpendicular to the edge.

Edge pairs are now identified by searching along the gradient direction out to a prespecified distance from each pixel; in our experiments, the distance was 10. We are interested in pairs of edges that are on opposite sides of a "primitive"; hence we want them to have approximately opposite slopes. Specifically, when the starting edge pixel has slope $45i°$, we consider that an edge pair has been detected if the edge found by the search has slope $45(i+3)°$, $45(i+4)°$, or $45(i+5)°$ modulo $360°$. Such edge pairs are sometimes called "anti-parallel", because their slopes differ by approximately $180°$. The search takes place on both the dark side and the light side of each edge pixel.

For each edge pair, we compute the following quantities:

1) The distance $d(1 \le d \le 10)$ between the edges
2) The average gray level μ on the line segment between the edges
3) The standard deviation σ of gray level on that line segment
4) The absolute difference δ between the slopes of the edges ($\delta=0°$ or $45°$)
5) The absolute difference Δ between the contrasts of the edges

Each of these quantities is computed separately for edge pairs found by searching on the light side and on the dark side of each edge pixel. We will denote the light-side quantities by unprimed symbols and the dark-side quantities by primed symbols ($d',\mu',\sigma',\delta',\Delta'$). Before computation of μ and σ (or μ' and σ'), histogram flattening is applied to the image.

The means of the primed and unprimed quantities just defined, computed over the given texture sample, will be used as texture measures. These measures will be denoted by Md, $M\mu$, $M\sigma$, $M\delta$, and $M\Delta$ (with and without primes). The variances of the distance measures (d and d') will also be used; these will be denoted by Vd and Vd'. However, it turns out that they do not perform as well as the means for most of the textures used in our experiments.

2.2. Curvature

The curvature-based measures are computed by least-squares fitting a quadratic surface to the gray levels in a 5-by-5 neighborhood of each pixel, after first median filtering and rescaling the image as in Section 2.1. This fitted surface defines the gradient magnitude and direction and the curvature (=rate of change of gradient direction) at the given pixel. Specifically, if the x and y partial derivatives of the fitted surface f are f_x and f_y, respectively, then the gradient magnitude is $\sqrt{f_x^2+f_y^2}$, the gradient direction is $\tan^{-1}(f_y/f_x)$, and the curvature is

$$\frac{f_{xx}f_y^2+f_{yy}f_x^2-2f_xf_yf_{xy}}{(f_x^2+f_y^2)^{3/2}}$$

(The direction and curvature are in radians; they are converted to degrees by multiplying them by 180°/π.) For further details on how these results are derived, see [8].

Nonmaximum suppression is then performed on the gradient magnitudes out to distance 2 in the gradient direction - in other words, a magnitude is ignored if a higher magnitude exists within distance 2 of it in that direction (on either side). Using the absolute curvatures at these gradient maxima, we compute two measures: the mean MC and the variance VC. Two other measures (denoted by primes) are computed using the curvatures "weighted" by their corresponding gradient magnitudes. Specifically, we construct a histogram of the absolute curvatures in which each pixel contributes a count to the histogram equal to the gradient magnitude of that pixel, rather than a count of 1. We then compute the mean MC' and the variance VC' of the histogram.

3. Experiments

To study the power of these measures to discriminate among textures, we applied them to samples of three geological terrain types: Mississippian limestone and shale, lower Pennsylvanian shale, and Pennsylvanian sandstone and shale, and two textures (raffia and sand) from Brodatz's album [9]; these textures have also been used in earlier texture classification experiments [3,4,7,10]. Each sample was 64 by 64 pixels; there were eight samples each of the terrain textures and four each of the Brodatz textures.

The terrain samples are shown in Figures 1-3, and the Brodatz samples in Figures 4-5; all samples are shown after median filtering and gray level rescaling. The corresponding thresholded, nonmaximum-suppressed edges are shown in Figures 6-10. The effects of the median filtering step are illustrated in Figure 11, in which the left column shows one of the terrain samples (the sixth one in Figure 2) after 0,1, and 2 iterations of median filtering followed by gray level rescaling. The center column shows the edge magnitudes after thresholding, and the right column shows them after nonmaximum suppression. Significant "cleaning" is evident on the edges obtained after median filtering.

Figure 12 shows scatter plots of the values of each of our measures for the terrain samples. In each plot, the three terrain types are denoted by M, L, and P, respectively; a "2" means that two samples yielded the same measured value. For comparison, scatter plots of the values of two measures based on second-order gray level probability densities are also given. (The joint gray level probabilities for a pair of pixels at relative displacement (1,0) were computed; CONX is the moment of inertia of the matrix of these probabilities around its main diagonal. CONY is defined analogously using displacement (0,1). Both CONX and CONY performed very well in earlier studies [10] using the terrain textures.) Scatter plots are also given for two of the measures, $M\mu$ and $M\mu'$, when histogram flattening was not used in computing them; we see that this results in much poorer separation of the classes.

Each measure was evaluated for a given pair of textures by the largest number of samples of the two textures that could be correctly classified by thresholding the value of the measure. The results are shown in the first three columns of Table 1. We see that

a) For each pair of textures, three or more of the measures yield 14 or 15 out of 16 correct.

b) The variance features do not perform any better than the mean features.

c) The features $M\delta$ and $M\delta'$, which (like the features used by Davis et al.) are based on pairs of edge slopes, perform relatively poorly.

d) The CONX and CONY features also perform relatively poorly.

Moreover, the values of the measures can often be directly related to visual properties of the textures, although the differences for these terrain textures are relatively slight.

Figure 13 shows analogous plots for the Brodatz samples (R=raffia, S=sand). Here, as summarized in the fourth column of Table 1, many of the measures yield perfect separation (and as we see from the scatter plots, often very wide separation) between raffia and sand; but the $M\delta$ and $M\delta'$, CONX and CONY measures do not. The perceptual significance of the features is usually quite obvious in this case. In another experiment, the Brodatz raffia texture was classified against all three terrain textures, and many features yielded perfect (28 out of 28) classification, including MC, MC', VC', and CONX.

4. Concluding remarks

The texture measures proposed in this paper are relatively easy to compute, since they are directly derived from edges and pairs of edges, and do not require explicit extraction of "primitives" as connected regions. At the same time, they are mathematically simple, being based on means of differences rather than on second-order statistics, and they also have simple perceptual interpretations. In our experiments, these measures performed better than various standard measures based on pairs of gray levels or pairs of edge orientations. For all these reasons, the proposed measures seem to deserve serious consideration for texture classification and analysis applications.

Measure	M/L	M/P	L/P	R/S
Md	11	*14	13	5
Md'	*15	*14	11	8
Mμ	12	*14	10	8
Mμ'	*14	13	11	8
Mσ	12	*14	13	5
Mσ'	*15	*15	11	8
Mδ	11	11	10	7
Mδ'	12	12	11	6
MΔ	12	13	*14	7
MΔ'	12	11	*14	8
MC	11	13	*14	8
MC'	11	*14	*14	8
Vd	11	11	9	8
Vd'	11	13	11	6
VC	12	12	13	7
VC'	10	12	13	8
CONX	13	13	10	7
CONY	11	13	12	6

Table 1. Number of samples of a given pair of textures that were correctly classified by each measure using the best possible threshold.

References

1. R. M. Haralick, Statistical and structural approaches to texture, Proc. IEEE 67, 1979, 786-805.

2. J. T. Maleson, C. M. Brown, and J. A. Feldman, Understanding natural textures, Proc. DARPA Image Understanding Workshop, October 1977, 19-27.

3. S. Wang, F. R. D. Velasco, A. Wu, and A. Rosenfeld, Texture primitive statistics for texture discrimination, IEEE Trans. Systems, Man, Cybernetics 11, 1981, in press.

4. T. H. Hong, C. R. Dyer, and A. Rosenfeld, Texture primitive extraction using an edge-based approach, ibid. 10, 1980, 659-675.

5. L. S. Davis, S. A. Johns, and J. K. Aggarwal, Texture analysis using generalized co-occurrence matrices, IEEE Trans. Pattern Analysis Machine Intelligence 1, 1979, 251-259.

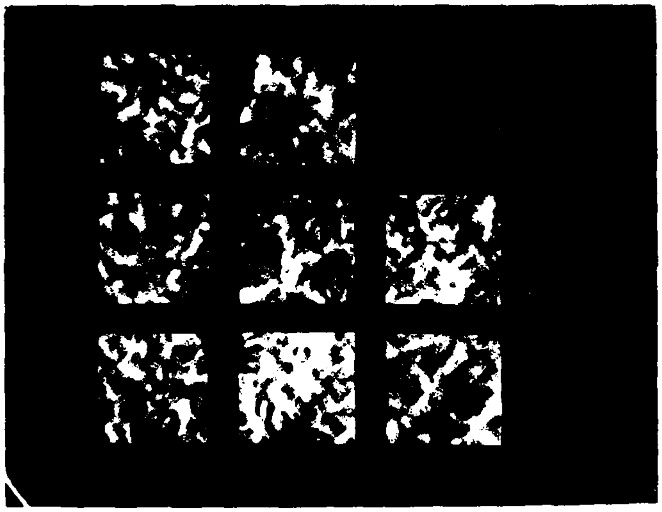
6. L. S. Davis, M. Clearman, and J. K. Aggarwal, An empirical evaluation of generalized cooccurrence matrices, ibid. 3, 1981, 214-221.

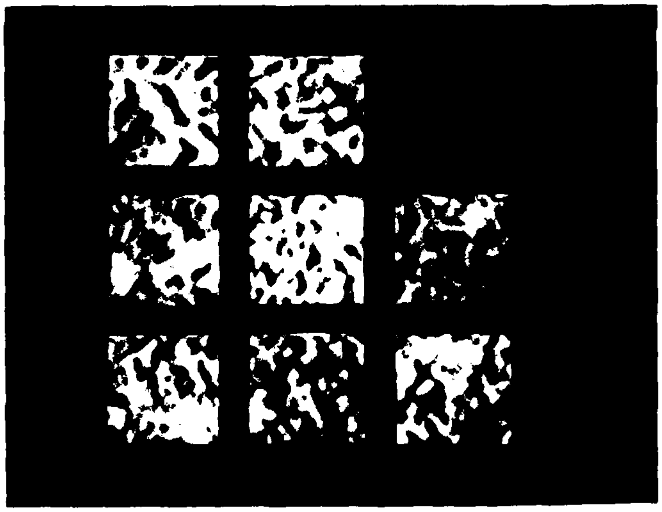
7. T. H. Hong, C. R. Dyer, and A. Rosenfeld, Texture classification using gray level cooccurrence based on edge maxima, IEEE Trans. Systems, Man, Cybernetics 10, 1980, 156-163.

8. L. Kitchen and A. Rosenfeld, Gray level corner detection, TR-887, Computer Vision Laboratory, Computer Science Center, University of Maryland, College Park, MD, April 1980.

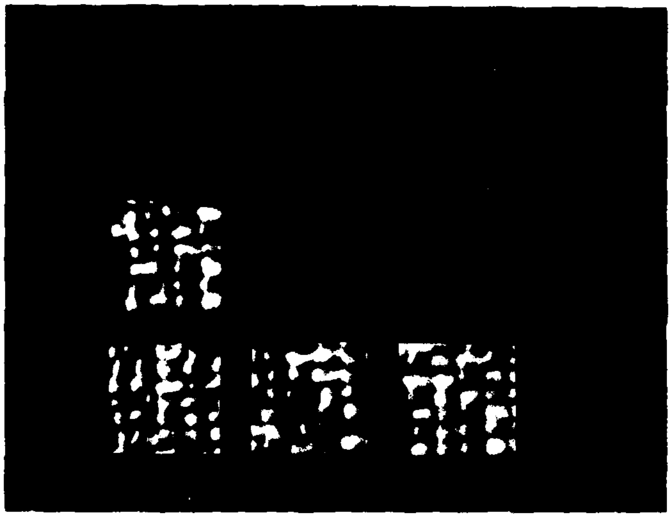
9. P. Brodatz, Textures: A Photographic Album for Artists and Designers, Dover, New York, 1966.

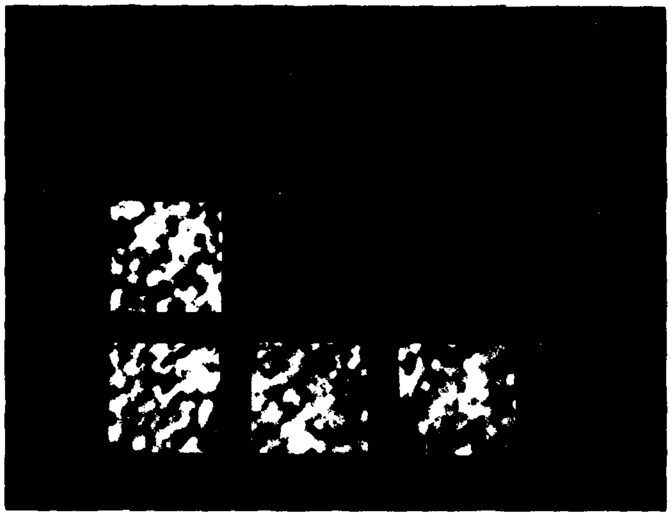
10. J. S. Weszka, C. R. Dyer, and A. Rosenfeld, A comparative study of texture measures for terrain classification, IEEE Trans. Systems, Man, Cybernetics 6, 1976, 269-285.



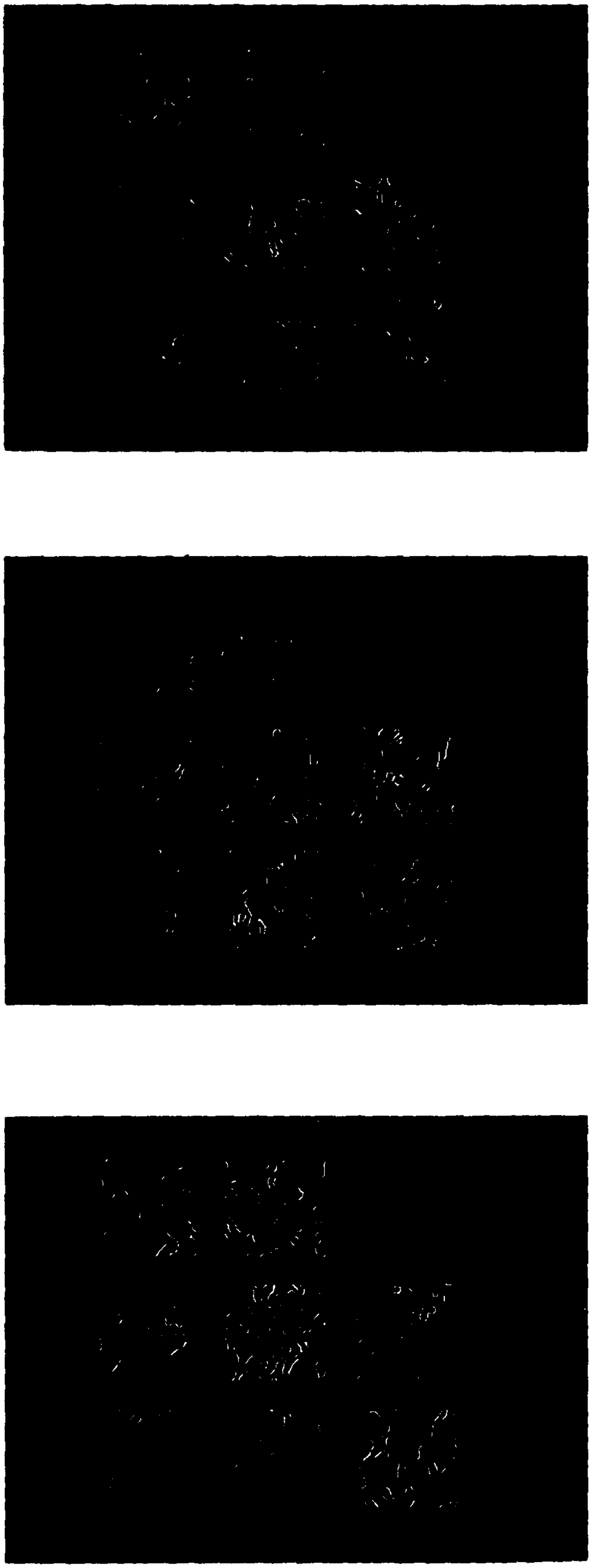


Figures 1-3. Terrain samples.

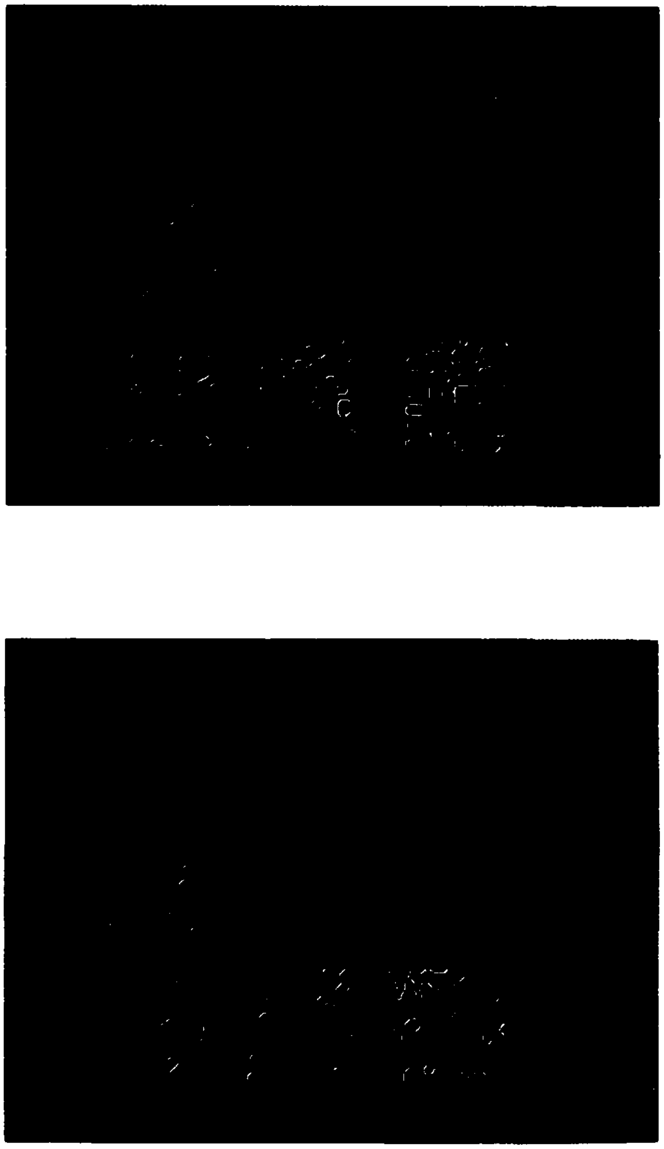




Figures 4-5. Brodatz samples: Raffia (top), sand (bottom).



Figures 6-8. Edges for Figs. 1-3.



Figures 9-10. Edges for Figs. 4-5.

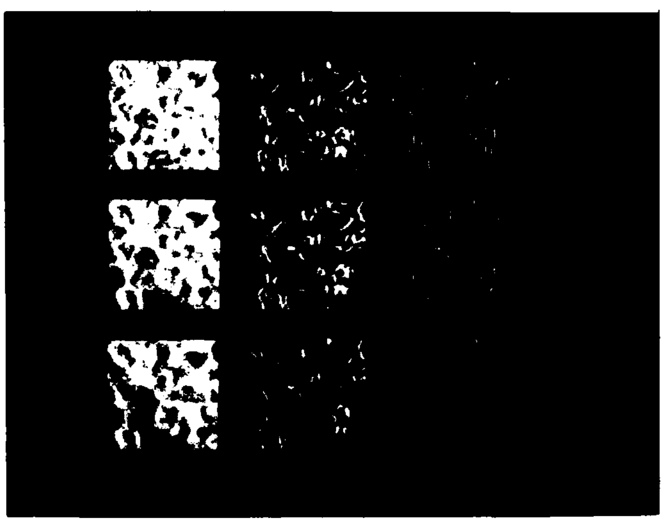


Figure 11. Effects of median filtering.

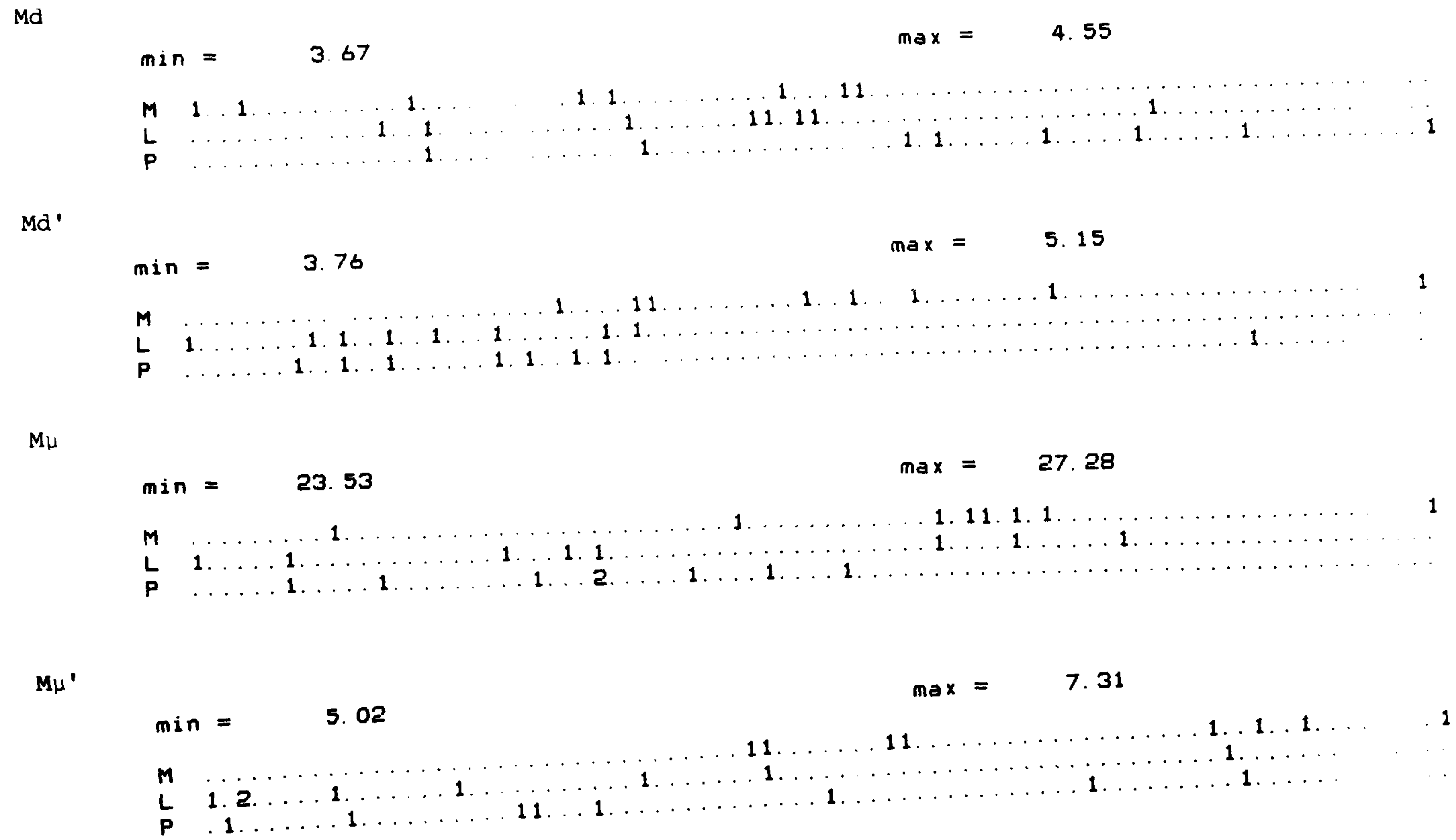


Figure 12. Scatter plots of measure values for the terrain textures (M=Mississippian, L=Lower Pennsylvanian, P=Pennsylvanian).

```
Mσ
     min =      2.74                                          max =      3.55

     M  11......1..........1.1.........1...1....1.................................
     L  .........1.................1..1...1111..................1....................
     P  .........................1.1....................1...1..1.......1.......1......1

Mσ'
     min =      2.78                                          max =      4.15

     M  ..........................1.11.........1...1..1.........1......................1
     L  1......1.1..1..1...1......1...1.............................................
     P  .......1..11....1..1...2.........................................1..........

Mδ
     min =      19.76                                         max =      25.86

     M  1.......................11...........1...........11.11....................
     L  ......................1.....1......1..1.........1......1...1..............1
     P  ..................1....................1..1..1........12...................1...

Mδ'
     min =      21.38                                         max =      26.37

     M  ....2..............1.1..1........1.....................1..........1.......
     L  ...................1.....2...1.....1......1...1.......................1.......
     P  1.....................................1.....1.....1........2..1..............1
```

Figure 12, cont'd.

MΔ

```
min =      6.01                                max =    15.20

M  ....3.......1............12..................................................1
L  1.........11...111.....2.......................................................
P  ..............1.....1.....1...1...........1...2..............1................
```

MΔ'

```
min =      6.25                                max =    15.74

M  1.......11...............11............1...........1..........................1
L  ........1....111.21......1.....................................................
P  .................1..1.1.12..........1..1.......................................
```

MC

```
min =      .5.51                               max =    20.27

M  .......................1.............1..1.....1.......1...1..............1......1
L  ......................................................1..1...2.1...1...2..........
P  1....1............1............11..1...................1..............1........
```

MC'

```
min =      12.58                               max =    17.18

M  .......................................1.1...11..1......1.................1...1
L  ........................................1.....1..1.12.............1....1.........
P  1................1...............11...1...11.......................1............
```

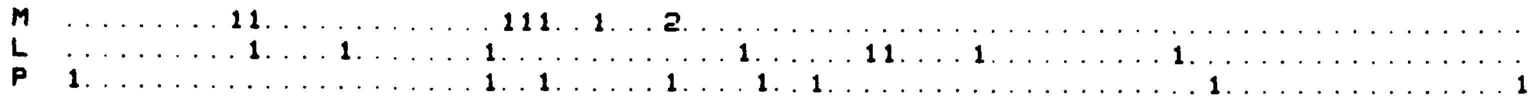
Figure 12, cont'd.

```
Vd

    min =       2.92                                     max =      4.27

    M  11...............1.....1..........1......1............1.......1..................
    L  ....................1....1....1.............1....1.....1........1...............1
    P  ...............1.........1........1...........1..1.1.....1.................1.....


Vd'

    min =       2.78                                     max =      5.00

    M  ....................11..............1........1......1.1............1............1
    L  ..................11..1...1......1..........1............1............1..........
    P  1.........1...........1.11.........1...11........................................

VC

    min =     242.10                                     max =    439.50

    M  ..................1...............1.....11..1....1..................1.........1..
    L  .....................................1.......11..1..111....1.....................
    P  1..1............1........1.......1.........1.........................1..........1

VC'

    min =     162.80                                     max =    260.60

    M  .......................1........1......1...........1.....12.....1................
    L  ...................................1............1...11.2............1...........1
    P  1..........2..........1.....1................1..........1.......1................
```

Figure 12, cont'd.

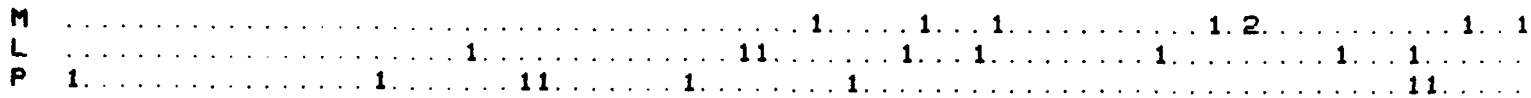
CONX

min = 68.90 max = 135.25



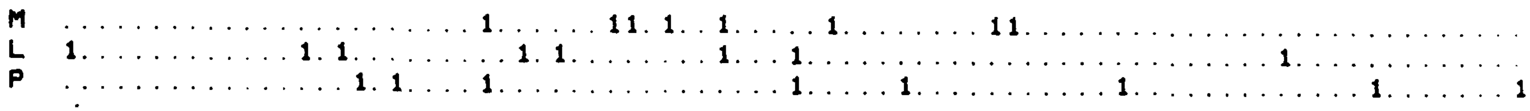
CONY

min = 62.96 max = 92.19



Mμ*

min = 16.87 max = 24.02



Mμ'*

min = 7.03 max = 11.74

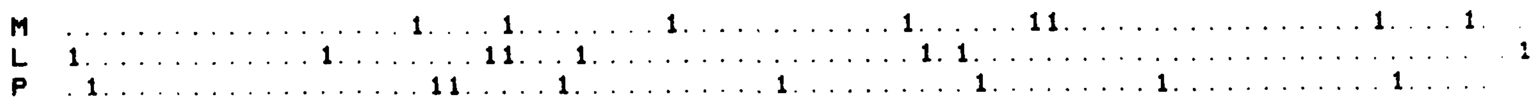


Figure 12, cont'd.

*Computed without histogram flattening.

```
Md

     min =      4.48                                         max =      5.63

     R  1..........................................................1....1.......1..................
     S  ...................................................1......1.......1...................1

Md'

     min =      3.90                                         max =      4.77

     R  .................................................................................1.....1....2
     S  1....1.....................1......1..............................................

Mμ

     min =      22.52                                        max =      25.77

     R  ............................................................1...............1.........1.....1
     S  1.........................1.....1......1..........................................

Mμ'

     min =      4.62                                         max =      7.25

     R  ....................................................................1.............1........1.1
     S  2.................................2..................................................
```

Figure 13. Scatter plots of measure values for the Brodatz textures(R=raffia, S=sand).

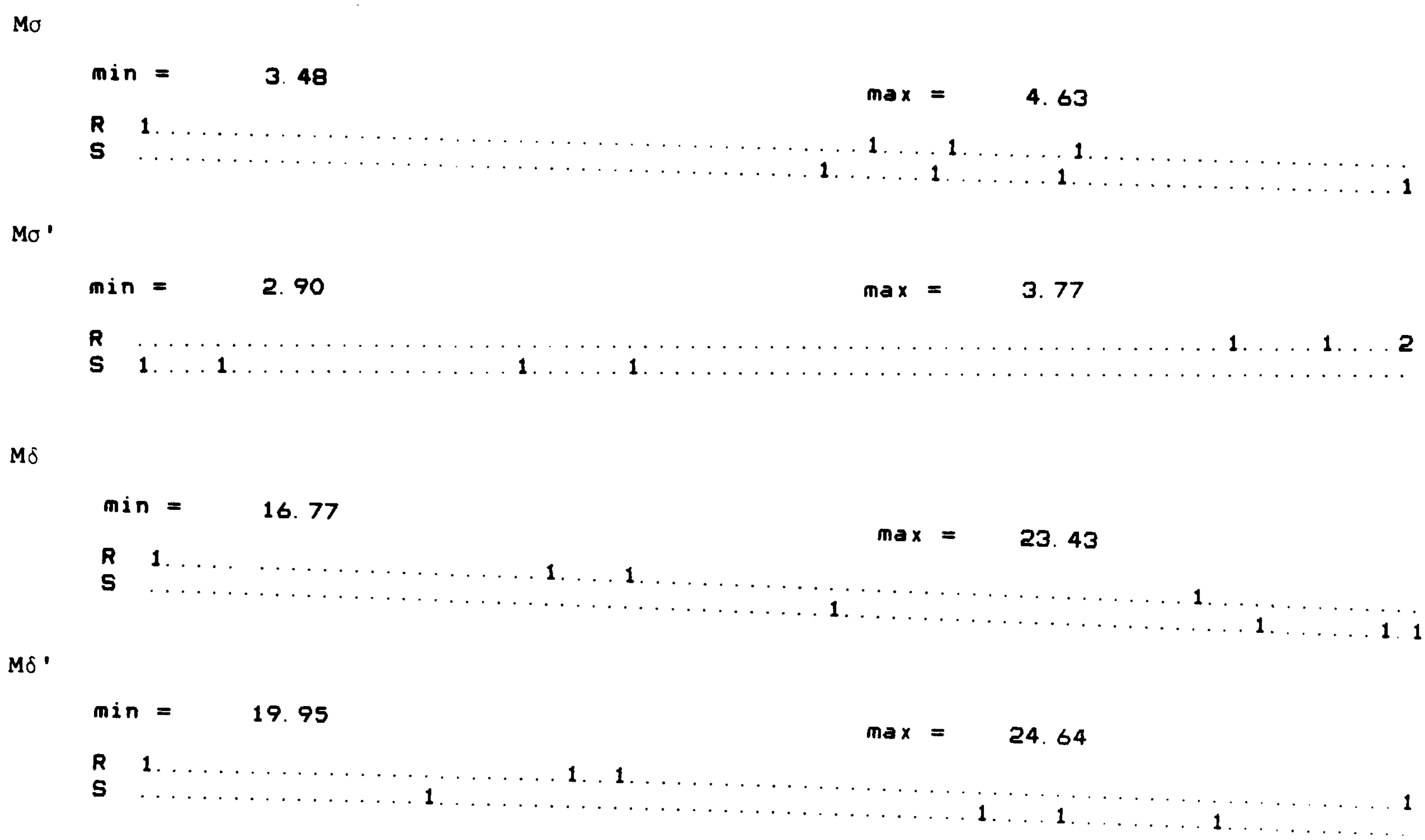


Figure 13, cont'd.

```
MΔ

     min =      8.73                                   max =    12.21

     R  ..................1..........................1.......1.........1
     S  11.............................1.......1.......................

MΔ'

     min =      7.70                                   max =    14.60

     R  ..........................1...................2..............1
     S  1.1...............11..........................................

MC

     min =     13.21                                   max =    17.40

     R  11....1.................1....................................
     S  ..........................................1..1......1........1

MC'

     min =     12.00                                   max =    14.89

     R  1......11.....1..............................................
     S  ........................................1....1....1.........1
```

Figure 13, cont'd.

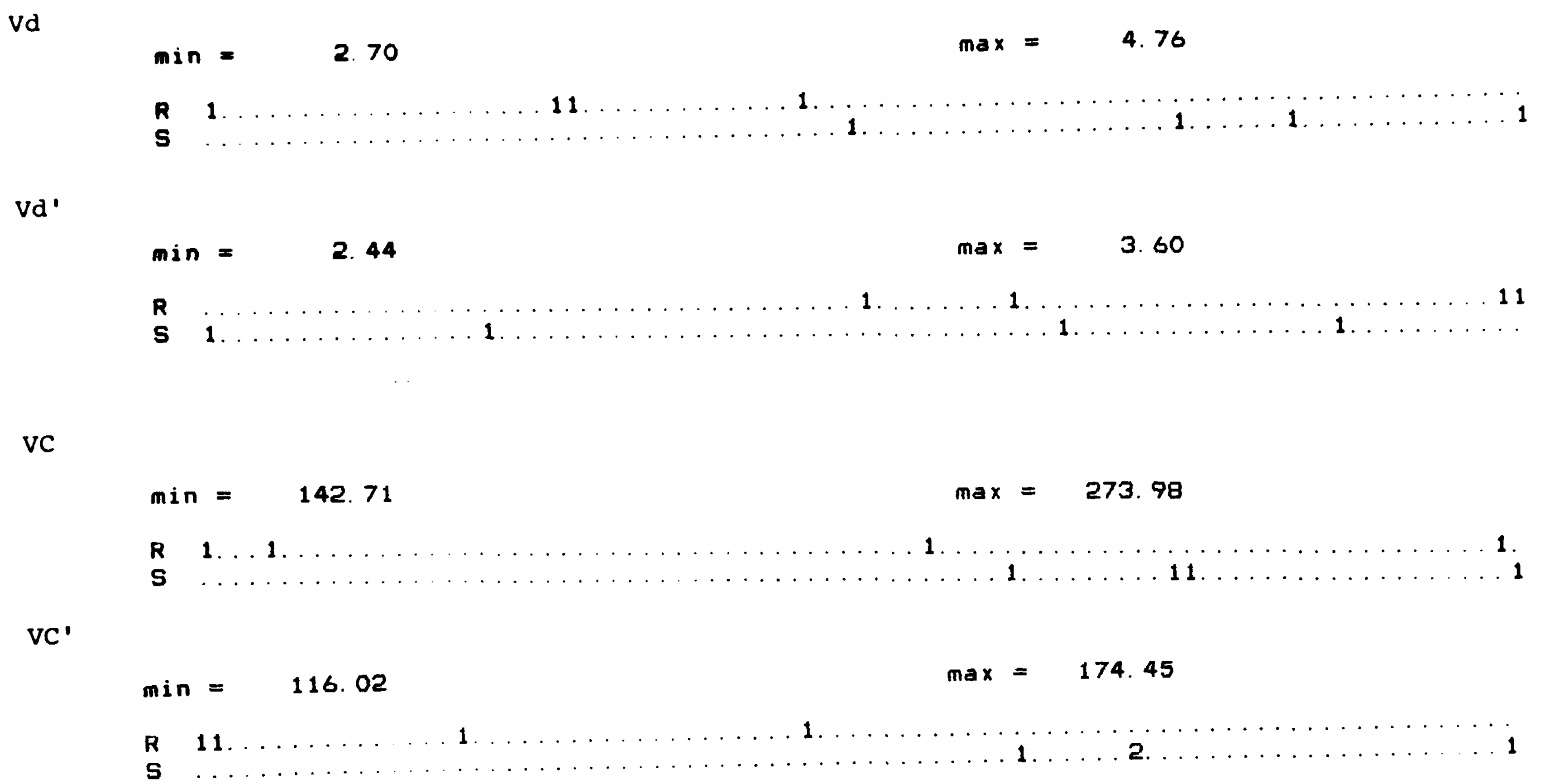


Figure 13, cont'd.

```
CONX

     min =      42.05                                     max =     77.63

     R  1...............1..1.......................1....................................
     S  .......................1....1.................................1................1

CONY

     min =      47.50                                     max =     75.99

     R  .......................................1........1.........................1.....1
     S  1.1.......................................1....................1................
```

Figure 13, cont'd.

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A class of texture measures is introduced based on first-order statistics derived from edges in the image. These measures are related to the generalized cooccurrence features of Davis et al. They yield good discriminations among textures on perceptually plausible grounds.

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